CONVOLUTIONAL NEURAL NETWORKS

What the neural network is: A Convolutional Neural Network (CNNs) is a type of neural network specifically built to handle grid-structured data like images.[1] They are especially effective for tasks involving image analysis and recognition.[1] key components of a convolutional neural network are convolutional layers, pooling layers, activation function, and fully connected layers.[1] It is a type of feedforward neural network that learns to extract features by optimizing filters (also known as kernels).[2] This deep learning architecture has been widely used to analyze and make predictions from various data types, including images, text, and audio.[2] CNNs have become the standard approach for tasks in computer vision and image processing, although newer architectures like transformers have started to replace them in certain applications.[2]

How it works:

1. **Input Layer:** The CNN takes an input image, which is often preprocessed to ensure uniformity in size and format.[3]
2. **Convolutional Layer:** This is the core layer where most of the computation occurs.[3] It uses a filter (or kernel) to scan the input image, applying a dot product between the filter and the image's pixels.[3] As the filter moves (or "convolves") over the image, it produces a feature map, which highlights specific features such as edges, textures, or shapes.[3] The filter weights are shared across the entire image, and some of the weights are updated during training.[3]
3. **Hyperparameters:** In the convolutional layer, there are several hyperparameters that affect the output:
    a. **Number of filters** determines the depth of the feature map.[3]
    b. **Stride** controls how much the filter moves at each step, influencing the size of the output.[3]
    c. **Padding** (valid, same, or full) can be applied to handle situations where the filter does not fit perfectly within the input image.[3]
4. **ReLU Activation:** After each convolution operation, a Rectified Linear Unit (ReLU) function is applied to introduce nonlinearity into the model, allowing it to learn more complex patterns.[3]
5. **Additional Convolutional Layers:** If there are multiple convolutional layers, they form a hierarchical structure.[3] Earlier layers detect basic features (e.g: edges), while deeper layers combine these features to recognize more complex patterns (e.g: objects or parts of an object, like a bicycle).[3]
6. **Pooling Layer:** This layer reduces the dimensionality of the feature maps to decrease the number of parameters and computation.[3] It uses filters without weights, applying functions like max pooling (selects the maximum value in the receptive field) or average pooling (calculates the average value).[3] Pooling helps improve efficiency and prevent overfitting.[3]
7. **Fully Connected (FC) Layer:** After the convolutional and pooling layers, the feature maps are flattened and passed into the fully connected layer.[3] In this layer, every node is

connected to every node from the previous layer.[3] The FC layer uses an activation function (often softmax) to classify the image, producing a final prediction, such as the probability of the image belonging to a specific class.[3]

8. **Output:** The CNN's final output is a prediction, like identifying the class of the image (e.g: recognizing an object or a pattern).[3]

How it is used/ Applications:

1. **Classification:**
    a. CNNs classify lung nodules on CT scans as benign or malignant.[4]
    b. 2D-CNNs classify liver masses using triphasic CT images.[4]
    c. Classify nodules using full 3D spatial information with 3D patches.[4]
    d. Utilize multiphase CT or MRI (e.g: arterial, delayed phases) for better diagnostic performance.[4]
2. **Segmentation:**
    a. Segment organs (like the uterus or liver) and tumors in MRI/CT images.[4]
    b. Generate probability maps of organ presence and refine using algorithms like graph cut.[4]
    c. Separately segments liver and liver mass for improved efficiency.[4]
3. **Detection:**
    a. 2D-CNNs (AlexNet, GoogLeNet) used for detecting TB in chest X-rays.[4]
    b. CNN-based CADe systems outperform traditional feature-based detection systems.[4]
    c. Use of radiologist annotations and unsupervised clustering with CNNs (e.g: Faster R-CNN) to detect lesions more accurately.[4]

Challenges/ Any gotchas in using it:

- **Lack of Explainability:** CNNs are often considered a "black box" because they do not provide a clear explanation of how they arrive at their decisions, making it difficult to understand what features are responsible for predictions.[4]
- **Vulnerability to Adversarial Examples:** CNNs are susceptible to adversarial examples, which are carefully crafted inputs that cause the network to make incorrect predictions without any visible change to the image.[4] This is a concern, especially in medical imaging, where robustness is critical.[4]
- **Need for Large, Well-Annotated Datasets:** Effective deep learning models require large amounts of labeled data to perform well.[4] However, in the medical domain, building such datasets is costly, time-consuming, and may involve ethical and privacy issues.[4] The lack of sufficient high-quality datasets limits the performance of CNNs in medical imaging.[4]
- **Overfitting and Generalization Issues:** Deep learning models, including CNNs, can overfit to small or limited datasets, leading to poor generalization.[4] This is particularly problematic in medical imaging, where robust models are necessary for clinical use.[4]

References:

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